

J-A HYSTERESIS MODEL PARAMETERS ESTIMATION USING GA

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Summary This paper presents the Jiles and Atherton (J-A) hysteresis model parameter estimation for soft magnetic composite (SMC) material. The calculation of Jiles and Atherton hysteresis model parameters is based on experimental data and genetic algorithms (GA). Genetic algorithms operate in a given area of possible solutions. Finding the best solution of a problem in wide area of possible solutions is uncertain. A new approach in use of genetic algorithms is proposed to overcome this uncertainty. The basis of this approach is in genetic algorithm built in another genetic algorithm.

1. INTRODUCTION

J-A hysteresis model is one of the most investigated hysteresis model in recent years focusing on estimation of five model parameters using different optimization techniques. One of these techniques are well known genetic algorithm. To determine five J-A model parameters it is adequate having only one measured hysteresis loop [1]. For this purpose the measured DC hysteresis loops were obtained. Fig. 1 shows the measured DC hysteresis loop for soft magnetic composite material Somaloy 500TM [2] at different induction levels.

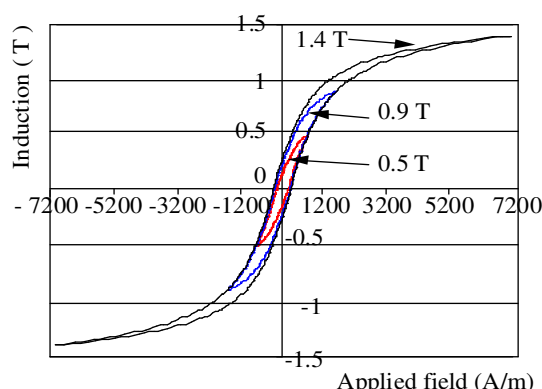


Fig. 1. Measured DC curves at different induction levels.

The DC hysteresis loop measured values from Fig. 1 at induction level 1.4 T are going to be further used to optimize five J-A model parameters.

2. FERROMAGNETIC J-A HYSTERESIS MODEL

Mathematical model for ferromagnetic hysteresis introduced by Jiles and Atherton (J-A model) is based on physical principles of ferromagnetic material and not strictly on mathematical or experimental curve fitting [3]. The J-A model assumes that total magnetization M of ferromagnetic material is decomposed into an irreversible M_{irr} and a reversible M_{rev} magnetization component [3], [4].

The form of total differential magnetization susceptibility dM/dH is:

$$\frac{dM}{dH} = (1-c) \frac{M_{an} - M_{irr}}{k\delta - \alpha(M_{an} - M_{irr})} + c \frac{dM_{an}}{dH}, \quad (1)$$

where M_{an} is anhysteretic magnetization curve represented by Langevin function:

$$M_{an} = M_s \left[\coth\left(\frac{H + \alpha M}{a}\right) - \frac{a}{H + \alpha M} \right]. \quad (2)$$

Five material – dependent parameters appearing in (eq. 1) and (eq. 2) are:

M_s – magnetization saturation,
 a – shape parameter,
 α – main field parameter,
 k – domain wall pinning constant, proportional to hysteresis losses,
 c – domain flexing constant.

The parameter δ has no physical meaning and is equal to +1 for $dH/dt > 0$ and to -1 otherwise. The induction B can be calculated using:

$$B = \mu_0 (H + M). \quad (3)$$

At first the optimization of five parameters included in J-A model is done using measured results of hysteresis loops and by genetic algorithms.

3. GENETIC ALGORITHMS FOR J-A MODEL PARAMETERS IDENTIFICATION

To get the best fitted modelled hysteresis (J-A hysteresis model parameters values) the genetic algorithms (GAs) are used.

The genetic algorithms are optimization technique based on the concept of natural selection and genetics [5]. The algorithm starts with a set of possible solutions – individuals called population

[5], [1]. Solutions from a population are used to form a new population by hope that the new population will be better than the old one. Solutions that will form a new set of solutions are selected according to their fitness. This is repeated until stop criteria (for example, number of generations or improvement of the best solution) is satisfied.

The GAs can optimize with continuous or discrete parameters and can handle numerically generated data, experimental data or analytical functions [1].

The construction of population for J-A models parameters used in GAs for optimization process is shown on Figure 2 [1].

$$pop = \begin{bmatrix} a_1 & \alpha_1 & k_1 & Ms_1 & c_1 & fitness_1 \\ M & M & M & M & M & M \\ M & M & M & M & M & M \\ a_n & \alpha_n & k_n & Ms_n & c_n & fitness_n \end{bmatrix}$$

Fig. 2. Construction of population.

n – number of individuals included in population.

Each row of population represents one individual (chromosome), composed of parameters of J-A model called genes (column). The last column represents the estimation of the individual – fitness according to chosen evaluation of individual (for example, sum square error - SSE). In this case the fitness is obtained by difference between measured and computed induction B :

$$fitness = -abs \sum_{i=1}^m (Bm_i - Bc_i) \quad (4)$$

Bm – measured induction ,

Bc – calculated induction using J-A model,

m – number of measurements.

GAs searches for the best solution in an area of possible solutions individually determined for each parameter (Table 1). The area of possible solutions (searching area) is limited with upper and lower limit values. It is uncertain, if the global optimum exists in this limited area.

With selection, crossover and mutation methods as GAs operators in gaot Matlab toolbox, the new better population is formed. Selection function is based on the normalized geometric distribution. Crossover is arithmetic function that takes two

individuals and performs an interpolation along the line formed by the two individuals to get the new individual. Some individual genes are chosen to mutate using non-uniform probability distribution of mutation.

Using selected population (Fig. 2), estimation of fitness (eq. 4) and selected searching area (Tab. 1) with GAs the identification of J-A model parameters is done. The optimization results with 40 individuals after 100 generations of GAs on measured hysteresis loop with induction of 1.4 T are presented in Tab. 2.

Parameters	Upper area limit	Lower area limit
a	2000	100
α	0.002	0.0001
k	2500	100
Ms	$1.7 \cdot 10^6$	$1 \cdot 10^6$
c	0.3	0.01

Tab. 1. GAs parameter area limits for measured DC hysteresis loop $B = 1.4$ T.

J-A model parameters	Optimized values
a	694,684
α	0,000614
k	320,873
Ms	1149531,87
c	0,1469

Tab. 2. Optimized J-A model parameter values for measured DC hysteresis loop $B = 1.4$ T.

The results were not satisfied in spite of repeated calculations with GAs. The GAs did not find the global optimum in defined searching area. If taking the wide searching not clear in convergence of the best solution. In [1] is proposed to calculate the suitable ranges for the J-A model parameters with a trial-and-error procedure using a small number of individuals with few generations by observing the error (fitness).

From previous work with GAs the improve english with wide search area, is proposed. The main idea is to use genetic algorithm built in another genetic algorithm called GgaA. Flow diagram of GgaA is shown in Fig. 3.

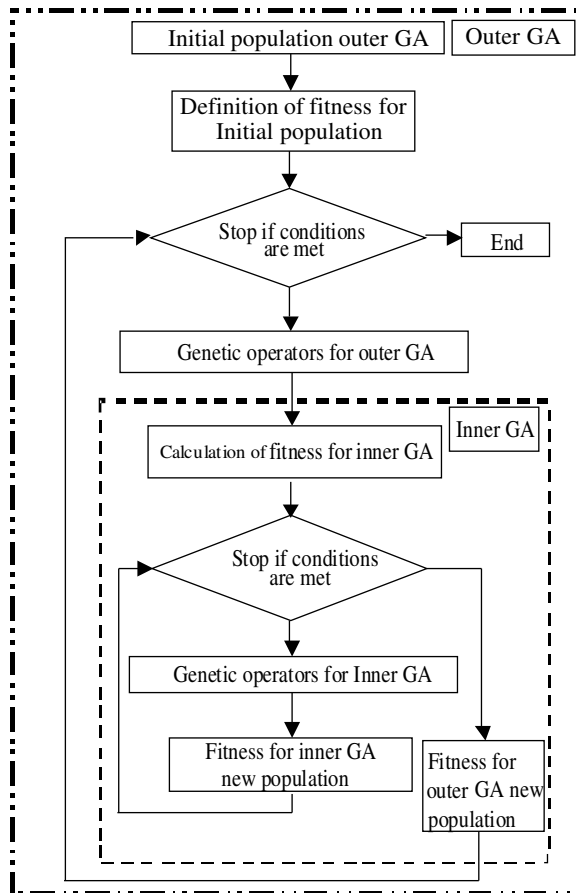


Fig. 3. Flow diagram of GgaA.

The main property of GgaA is, that the outer GA finds the best upper and lower searching area limits and inner GA is used to estimate the fitness. In fact from wide searching area the region containing global optimum is extracted out.

The outer GA individual of the population is composed with eleven genes, which represents upper and lower limits of search area plus fitness. For example, the first gene of individual represents the upper boundary area limit for parameter a , the second gene represents the lower boundary area limit for parameter a , and in the same manner further for the rest of parameters.

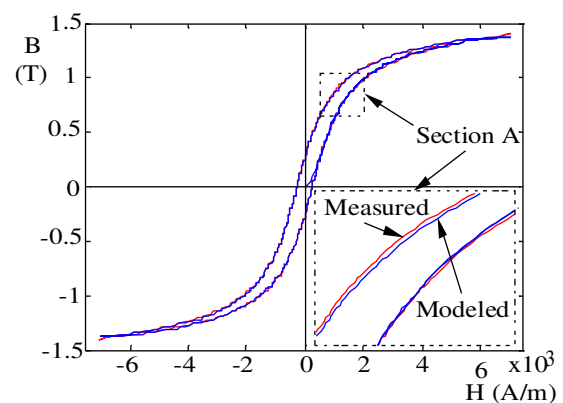
The inner GA uses 40 individuals and 100 generations. This number of individuals and generations is selected because the searching area of inner GA is narrow and is expected to find global optimum for all searching areas (fast convergence) delivered from outer GA. To determine the fitness for outer GA the inner GA finds the J-A model not clear for current area limits. It uses measured values of DC hysteresis loops and fitness from (eq. 4). Inner GA is also used when GgaA stopping conditions are reached (number of generations of outer GA). In this case the inner GA optimizes J-A model parameters with upper and lower limits of parameters searching area optimized with GgaA.

The J-A model parameter identification is done using new GgaA optimization way on measured hysteresis loop with induction of 1.4 T. The results are presented in Fig. 4, Tab. 3 and Tab. 4. Outer GA is set to 10 individuals and 20 generations.

Parameters of GgaA	Search area limits for GgaA
a upper limit	$4000 \div 1950$
a lower limit	$1950 \div 100$
α upper limit	$0,004 \div 0,00195$
α lower limit	$0,00195 \div 0,0001$
k upper limit	$4000 \div 1950$
k lower limit	$1950 \div 100$
Ms upper limit	$2,4 \cdot 10^6 \div 10^6$
Ms lower limit	$10^6 \div 0,4 \cdot 10^6$
c upper limit	$0,3 \div 0,1475$
c lower limit	$0,1475 \div 0,005$

Tab. 3. GgaA parameter area limits for measured DC hysteresis loop $B = 1.4$ T.

J-A model parameters	Search area limits optimized with GgaA	Optimized values with inner GA
a	$1974,577 \div 124,577$	1188,541
α	$0,00197 \div 0,000121$	0,001633
k	$1974,577 \div 137,744$	322,618
Ms	$1,6 \cdot 10^6 \div 0,9 \cdot 10^6$	$1,268 \cdot 10^6$
c	$0,2479 \div 0,04657$	0,2220997

Tab. 4. Optimized J-A model parameter values for measured DC hysteresis loop $B = 1.4$ T using GgaA.Fig. 4. Optimization result of GgaA for measured DC hysteresis loop $B = 1.4$ T

From Fig. 4 it can be seen that modelled hysteresis loop is very well fitted to the measured one. Discussion does not exist and work done with GgaA's.

4. CONCLUSION

The identification of J-A hysteresis model parameters with genetic algorithms for SMC material is efficient method when searching area is pre defined with knowledge of possible solutions. Good possible solutions can be obtained from empirical equitation in characteristic points on hysteresis loop delivered from (eq. 1) and (eq. 2) [6]. If no assumption on solutions is present and wide searching area range is selected the use of GgaAs approach gives good results. This is clearly seen from Figure 4. Obtained results are improve English of J-A hysteresis model for SMC material. Best-fitted hysteresis model parameters could be used to calculate hysteresis losses in SMC material.

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